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Multistage stochastic inexact chance-constraint programming for an integrated biomass-municipal solid waste power supply management under uncertainty

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ABSTRACT

In this study, a multistage stochastic inexact chance-constraint programming (MSICCP) model is developed for power supply management under uncertainties. In the MSICCP model, methods of multistage stochastic programming (MSP), interval-parameter programming (IPP), and chance-constraint programming (CCP) are introduced into a general optimization framework, such that the developed model can tackle uncertainties described in terms of interval values and probability distribution s over a multistage context. Moreover, it can reflect dynamic and randomness of energy resources during the planning horizon. The developed method has been applied to a case of managing the process of power supply in an integrated biomass-municipal solid waste power plant. Useful solutions for the power supply management have been generated. Interval solutions associated with different risk levels of constraint violation have been obtained. The generated solutions can provide desired energy resource allocation with a minimized system cost, maximized system reliability and a maximized energy security. Tradeoffs between system costs and constraint-violation risks can also be tackled. Higher costs will increase system stability, while a desire for lower system costs will run into a risk of potential instability of the management system. They are helpful for supporting (a) adjustment or justification of allocation patterns of energy resources, and (b) analysis of interactions among economic cost, environmental requirement, and power supply security.

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1. Introduction

With the rapid economic development and the improvement in people's living level, the demand for energy resources increases

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significantly [1]. As a main fuel for power generation, coal has been consumed in large amount. For example, in 2010, China's coal consumption in power generation industry has reached 0.91 billion metric tonnes, which accounts for 62.23 percent of the total amount of steam coals. In addition, it is estimated that it would exceed 1.4 billion metric tonnes in 2015. Besides, environmental pollution associated with the consumption of coal has a serious pressure on ecosystem and human health [2]. Therefore, it is extremely urgent to look for renewable energy resources which are favorable to environment protection and sustainable development, such as biomass and municipal solid waste (MSW).

However, considering the biomass or MSW utilization, a number of impact factors, such as low-density of biomass materials, low heating value, and low thermal efficiency and increasing energy demand, lead to an increasing consumption of energy resources. This would inevitably result in conflicts among economic objective, energy demand/supply, and environmental requirement. Therefore, several authors developed innovative systems or optimization techniques to take full advantage of biomass or MSW previously. For example, combining a biomass gasification power plant, a gas storage system and stand-by generators, Pérez-Navarro et al. [3] proposed an innovative hybrid wind-biomass system to stabilize a generic 40 MW wind park. A biogas, solar and a ground source heat pump greenhouse heating system (BSGSHPGHS) with horizontal slinky ground heat exchanger was designed innovatively by Esen and Yuksel [4] to meet the required heating load. Anderson et al. [5] developed a multi-objective evolutionary algorithm (specifically MOGA) to optimize the operation of a generic waste incineration plant in terms of economic and environmental goals, and operational constraints.

During the last decade, in order to promote the development of renewable energy resources in China, the investment in new energy is substantially on the rise, especially in biomass power industry. Based on the medium- to long-term development planning of renewable energy, Chinese Central People's Government has proposed the development goals for biomass power generation: by 2015, its installed capacity would be 13 GW (equivalent to generating capacity of 64.5 billion kWh); by 2020, its installed capacity will be 30 GW (equivalent to generating capacity of 148.8 billion kWh) [6]. Moreover, as a promising alternative way, the practice of MSW incineration for power generation is presently spreading in China, especially in cities where the economy is relatively more developed and landfill sites are difficult to locate [7].

In fact, with respect to biomass or MSW power generation, a variety of uncertain factors that should be considered by decision makers, including the acquisition of straw and stalks which are rather seasonal, the MSW generation rates, dynamics of system conditions, as well as the associated economic and technique parameters. In addition, many processes are linked to power generation, such as processing/conversion, transmission/storage, and supply/demand of electricity, further complicating the complexities in decisions making. Such uncertainties and complexities would affect the optimization process of MSW and biomass power generation and the generated decision schemes [8,9]. Above all, they could not effectively be addressed by the conventional deterministic optimization models. Therefore, it is desired to develop robust methods to deal with these uncertainties and complexities.

More recently, a number of inexact optimization techniques were developed to deal with such uncertainties and complexities in electric power and waste management systems. For instance, Li et al. [10] proposed a multistage interval-stochastic regional-scale energy model (MIS-REM) for supporting electric power system (EPS) planning under uncertainty. Li and Huang [11] presented a multistage interval-stochastic integer programming model for planning electric-power systems, where solutions of electricity-generation schemes under different GHG-mitigation options and electricity-demand levels were obtained. Li et al. [12] provided an interval-parameter two-stage stochastic mixed integer programming (ITMILP) model for waste management, which also could be used to analyze various policy scenarios that are associated with different levels of economic penalties when the promised policy targets are violated. Maqsood and Huang [13] introduced a two-stage interval-stochastic programming (TISP) model for the planning of solid-waste management systems, providing desired waste-flow patterns with minimized system costs and maximized system feasibility.

In general, the above discussion about electric power and MSW management systems mainly focus on several kinds of energy convention technologies (coal-fired power, wind power, biomass power, and solar power) and MSW management facilities (landfill, incineration, and composition). However, few studies were conducted on power supply management in a direct combustion biomass or MSW power plant, and hybridization of these two energy resources to adjust the power supply process on the base of taking the dynamic and randomness of biomass and MSW resources into account has received little attention. Moreover, although models mentioned above could effectively tackle uncertainties presented as both interval values and probabilistic distributions, they are incapable of accounting for the risk of violating uncertain system constraints, which means they can't support an in-depth analysis of the tradeoff between system cost and system-failure risk [14].

Thus, the objective of this study is to develop a multistage stochastic inexact chance-constraint programming (MSICCP) method and apply to a power supply management case with an integrated biomass-MSW power plant, reflecting the dynamic and randomness of energy resources. This is the first attempt that multistage stochastic programming (MSP), interval-parameter programming (IPP), and chance-constraint programming (CCP) methods are integrated into a general framework to manage the process of power supply under uncertainties and randomness presented as interval values and probabilities within a multi-stage context. A hypothetic case study was provided for demonstrating applicability of the developed method. The results can help decision makers identify the optimal power supply management strategies under uncertainty and gain a comprehensive tradeoff between system costs and constraint-violation risks. Moreover, to ensure the reliability and security of power supply, there are two types of power generation, including those utilizes biomass resources, as well as MSW-based backups [15].

2. Methodology

2.1. Multistage stochastic programming

In many real-world problems, uncertainties may be expressed as random variables, and the related study systems are of dynamic feature. Thus the relevant decisions must be made at each time stage under varying probability levels. Such a problem can be formulated as a scenario-based multistage stochastic programming (MSP) model with recourse. Uncertainties in MSP can be conceptualized into a multi-layer scenario tree (as shown in Fig. 1), with a one-to-one correspondence between the previous random variable and one of the nodes (state of the system) in each time stage (t) [16]. Generally, a multistage scenario-based stochastic linear programming model with recourse can be formulated as follows:

$$\max f = \sum_{t=1}^{T} \left(\sum_{j=1}^{n_1} c_{jt} x_{jt} - \sum_{j=1}^{n_2} \sum_{h=1}^{H_t} p_{th} d_{jth} y_{jth} \right) \tag{1a}$$

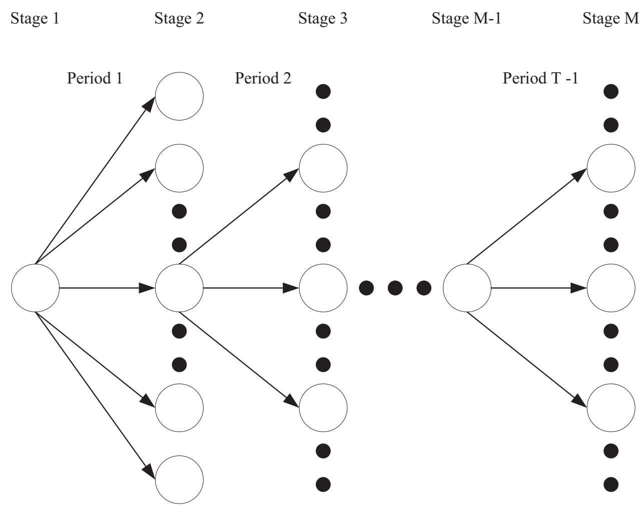

Fig. 1. Structure of a multistage scenario tree.

subject to

$$\sum_{j=1}^{n_1} a_{rjt}x_{jt} \le b_{rt}, r=1,2,...,m_1; t=1,2,...,T \tag{1b}$$

$$\sum_{j=1}^{n_1} a_{ijt}x_{jt} + \sum_{j=1}^{n_2} a'_{ijt}y_{jth} \le \hat{w}_{ith}, i=1,2,...,m_2; t=1,2,...,T; h=1,2,...,H_t \tag{1c}$$

$$x_{jt} \ge 0, j=1,2,...,n_1; t=1,2,...,T \tag{1d}$$

$$y_{jth} \ge 0, j=1,2,...,n_2; t=1,2,...,T; h=1,2,...,H_t \tag{1e}$$

where p_{th} is the probability of occurrence for scenario h in period t. "L", "M" and "H" denote the scenarios with low, medium, and high probability levels, respectively. Each scenario would correspond to a probability level p_{th} in each time period (e.g. L - L – L -…- L), with $p_{th} > 0$ and $\sum_{h=1}^{H_t} p_{th} = 1.\hat{w}_{ith}$ is random variable associated with probability p_{th}. In model (1), the decision variables are divided into two subsets. The x_{jt} represents the first-stage variables, which have to be decided before the random variables are disclosed; y_{jth} are related to the recourse actions against any infeasibilities after uncertainties are disclosed.

2.2. Inexact chance-constraint programming

The chance-constrained programming (CCP) method can effectively reflect the reliability of satisfying (or risk of violating) system constraints under uncertainty. In fact, the CCP method does not require that all of the constraints be totally satisfied. Instead, they can be satisfied in a proportion of cases with given probabilities [17]. A general stochastic linear programming problem can be formulated as follows:

$$\max C(t)X \tag{2a}$$

subject to

$$A(t)X \le B(t) \tag{2b}$$

$$x_j \ge 0, x_j \in X, j=1,2,...,n, \tag{2c}$$

where X is a vector of decision variables, and $A(t)$, $B(t)$, and $C(t)$ are sets with random element defined on a probability space $T, t \in T$[18,19]. To solve model (2), an 'equivalent' deterministic version can be defined. This can be realized by using a CCP approach, which consists of fixing a certain level of probability $p_i \in [0,1]$ for each constraint i and imposing the condition that the constraint is satisfied with at least a probability of $1-p_i$. The set of feasible solutions is thus restricted by the following constraints [18]:

$$\Pr\left[\{t | A_i(t)X \le b_i(t)\}\right] \ge 1-p_i, A_i(t) \in A(t), i=1,2,...,m \tag{3}$$

which are generally nonlinear, and the set of feasible constraints is convex only for some particular distributions and certain levels of p_i, such as the case when (i) a_{ij} are deterministic and b_i are random (for all p_i values), (ii) a_{ij} and b_i are discrete random coefficients, with $p_i \ge \max_{r=1,2,...,R}(1-q_r)$, where q_r is the probability associated with realization r, or (iii) a_{ij} and b_i have Gaussian distributions, with $p_i \ge 0.5$[20]. When a_{ij} are deterministic and b_i are random for model (2), constraint (3) becomes linear:

$$A_i(t) \le b_i(t)^{(p_i)}, \ \forall i \tag{4}$$

where $b_i(t)^{(p_i)} = F_i^{-1}(p_i)$, given the cumulative distribution function of b_i, and the probability of violating constraint i. The problem with Eq. (4) can only reflect the case when A is deterministic. If both A and B are uncertain, the set of feasible constraints may become more complicated [21–24].

To reflect randomness of the objective function in model (2), an 'equivalent' deterministic objective is usually defined in the CCP approach. There are four main options: (i) optimization of mean values, (ii) minimization of variance or other dispersion parameters, (iii) minimization of risk, and (iv) maximization of the fractile (or Kataoka's problem) [20]. However, these considerations are unable to effectively handle independent uncertainties in c_j and communicate them into the constraints. One potential approach for better accounting for uncertainties in A, B and C is to incorporate the ILP within the CCP framework, where intervals are used for reflecting uncertainties in A and C. An ILP model can be defined as follows [25]:

$$\max f^{\pm} = C^{\pm}X^{\pm} \tag{5a}$$

subject to

$$A^{\pm}X^{\pm} \le B^{\pm} \tag{5b}$$

$$X^{\pm} \ge 0 \tag{5c}$$

where $A^{\pm} \in \{\Re^{\pm}\}^{m\times n}$, $B^{\pm} \in \{\Re^{\pm}\}^{m\times 1}$, $C^{\pm} \in \{\Re^{\pm}\}^{n\times 1}$, and $\Re^{\pm}$ denotes a set of intervals. Let a denote a closed and bounded set of real numbers. An interval $a^{\pm}$ is defined as a range with known lower and upper bounds but unknown distribution: $a^{\pm} = [a^-, a^+] = \{t \in a | a^- \le t \le a^+\}$, where a^- and $a^{\pm}$ are the lower and upper bounds of $a^{\pm}$, respectively. This leads to a hybrid inexact chance-constrained programming (ICCP) model as follows:

$$\max f^{\pm} = C^{\pm}X^{\pm} \tag{6a}$$

subject to

$$\Pr[\{t | A_i^{\pm}X^{\pm} \le b_i(t)\}] \ge 1-p_i, A_i^{\pm} \in A^{\pm}, i=1,2,.....,m \tag{6b}$$

$$x_j^{\pm} \ge 0, x_j^{\pm} \in X^{\pm}, j=1,2,.....,n \tag{6c}$$

Model (6) can be converted into an 'equivalent' deterministic version as follows [18,26]:

$$\max f^{\pm} = C^{\pm}X^{\pm} \tag{7a}$$

subject to

$$A_i^{\pm}X^{\pm} \le B(t)^{(p)}, A_j^{\pm} \in A^{\pm}, i=1,2,.....,m \tag{7b}$$

$$x_j^{\pm} \ge 0, x_j^{\pm} \in X^{\pm}, j=1,2,.....,n \tag{7c}$$

where $B(t)^{(p)} = \{b_i(t)^{(p_i)} | i=1,2,...,m\}$.

2.3. Multistage stochastic inexact chance-constraint programming

Although model (1) can tackle uncertainties expressed as probability distributions and can provide a linkage between the pre-regulated policies and the associated economic implications, two limitations exist: (i) it is unable to handle independent uncertainties in both left-and right-hand sides of the constraints as well as coefficients of the objective function (i.e. A, B and C in model (5)); (ii) the linear constraints only correspond to cases when the left-hand coefficients are deterministic. Moreover, randomness in other right-hand-side parameters also needs to be reflected. Such uncertainties can be expressed as a minimum requirement on the probability of satisfying the constraints. This leads to a multistage stochastic inexact chance-constraint programming (MSICCP) model as follows:

$$\max f^{\pm} = \sum_{t=1}^{T}\left(\sum_{j=1}^{n_1} c_{jt}^{\pm} x_{jt}^{\pm} - \sum_{j=1}^{n_2}\sum_{h=1}^{H_t} p_{th} d_{jth}^{\pm} y_{jth}^{\pm}\right) \tag{8a}$$

subject to

$$\sum_{j=1}^{n_1} a_{rjt}^{\pm} x_{jt}^{\pm} \le b_{rt}^{\pm}, r=1,2,...,m_1; t=1,2,...,T \tag{8b}$$

$$\sum_{j=1}^{n_1} a_{ijt}^{\pm} x_{jt}^{\pm} + \sum_{j=1}^{n_2} a'_{ijt} \pm y_{jth}^{\pm} \le \hat{w}_{ith}^{\pm}, i=1,2,...,m_2; t=1,2,...,T; h=1,2,...,H_t \tag{8c}$$

$$\Pr\left\{\sum_{j=1}^{n_1} a_{sjt}^{\pm} x_{jt}^{\pm} + \sum_{j=1}^{n_2} a'_{ijt} \pm y_{jth}^{\pm} \le b_{st}\right\} \ge 1-p_s, s=1,2,...,m_3; t=1,2,...,T; h=1,2,...,H_t \tag{8d}$$

$$x_{jt}^{\pm} \ge 0, j=1,2,...,n_1; t=1,2,...,T \tag{8e}$$

$$y_{jth}^{\pm} \ge 0, j=1,2,...,n_2; t=1,2,...,T; h=1,2,...,H_t \tag{8f}$$

Constraint (8d) can be specified as follows:

$$\sum_{j=1}^{n_1} a_{sjt}^{\pm} x_{jt}^{\pm} + \sum_{j=1}^{n_2} a'_{ijt} \pm y_{jth}^{\pm} \le b_{st}^{(p_s)}, \forall s \tag{9}$$

In model (8), $x_{jt}^{\pm}$ represent the first-stage variables, which have to be decided before the actual realizations of the random variables; $y_{jth}^{\pm}$ denote second-stage variables, which are related to the recourses against any infeasibilities arising due to particular realizations of the uncertainties.

According to [27], based on the interactive algorithm, the MSICCP model can be converted into two deterministic submodels. The submodel corresponding to f^{+} can be formulated in the first step when the system objective is to be maximized; the other submodel (corresponding to f^{-}) can then be formulated based on the solution of the first submodel. Thus, the first submodel is formulated as follows:

$$\max f^{+} = \sum_{t=1}^{T}\left(\sum_{j=1}^{j_1} c_{jt}^{+} x_{jt}^{+} + \sum_{j=j_1+1}^{n_1} c_{jt}^{+} x_{jt}^{-} - \sum_{j=1}^{j_2}\sum_{h=1}^{H_t} p_{th} d_{jth}^{-} y_{jth}^{-} - \sum_{j=j_2+1}^{n_2}\sum_{h=1}^{H_t} p_{th} d_{jth}^{-} y_{jth}^{+}\right) \tag{10a}$$

subject to

$$\sum_{j=1}^{j_1} a_{rjt}^{-} x_{jt}^{+} + \sum_{j=j_1+1}^{n_1} a_{rjt}^{-} x_{jt}^{-} \le b_{rt}^{+}, r=1,2,...,m_1; t=1,2,...,T \tag{10b}$$

$$\sum_{j=1}^{j_1} a_{ijt}^{-} x_{jt}^{+} + \sum_{j=j_1+1}^{n_1} a_{ijt}^{-} x_{jt}^{-} + \sum_{j=1}^{j_2} a'_{ijt} - y_{jth}^{-} + \sum_{j=j_2+1}^{n_2} a'_{ijt} - y_{jth}^{+} \le \hat{w}_{ith}^{+}, i=1,2,...,m_2; t=1,2,...,T; h=1,2,...,H_t \tag{10c}$$

$$\sum_{j=1}^{j_1} a_{sjt}^{-} x_{jt}^{+} + \sum_{j=j_1+1}^{n_1} a_{sjt}^{-} x_{jt}^{-} + \sum_{j=1}^{j_2} a'_{ijt} - y_{jth}^{-} + \sum_{j=j_2+1}^{n_2} a'_{ijt} - y_{jth}^{+} \le b_{st}^{(p_s)}, \forall s \tag{10d}$$

$$x_{jt}^{+} \ge 0, j=1,2,...,j_1; t=1,2,...,T \tag{10e}$$

$$x_{jt}^{-} \ge 0, j=j_1+1, j_1+2,...,n_1; t=1,2,...,T \tag{10f}$$

$$y_{jth}^{-} \ge 0, j=1,2,...,j_2; t=1,2,...,T; h=1,2,...,H_t \tag{10g}$$

$$y_{jth}^{+} \ge 0, j=j_2+1, j_2+2,...,n_2; t=1,2,...,T; h=1,2,...,H_t \tag{10h}$$

where $x_{jt}^{\pm}$ $(j=1,2,...,j_1)$ are interval variables with positive coefficients in the objective function; $x_{jt}^{\pm}$ $(j=j_1+1, j_1+2,...,n_1)$ are interval variables with negative coefficients; $y_{jth}^{\pm}(j=1,2,...,j_2$ and $h=1,2,...,H_t)$ are random variables with positive coefficients in the objective function; $y_{jth}^{\pm}(j=j_2+1, j_2+2,...,n_2$ and $h=1,2,...,H_t)$ are random variables with negative coefficients. Solutions of $x_{jtopt}^{+}(j=1,2,...,j_1)$, $x_{jtopt}^{-}(j=j_1+1, j_1+2,...,n_1)$, $y_{jthopt}^{-}(j=1,2,...,j_2$ and$h=1,2,...,H_t)$, and $y_{jthopt}^{+}(j=j_2+1, j_2+2,...,n_2$ and $h=1,2,...,H_t)$ can be obtained from submodel (10). Based on the above solutions, the second submodel corresponding to f^{-} can be formulated as follows:

$$\max f^{-} = \sum_{t=1}^{T}\left(\sum_{j=1}^{j_1} c_{jt}^{-} x_{jt}^{+} + \sum_{j=j_1+1}^{n_1} c_{jt}^{-} x_{jt}^{-} - \sum_{j=1}^{j_2}\sum_{h=1}^{H_t} p_{th} d_{jth}^{+} y_{jth}^{-} - \sum_{j=j_2+1}^{n_2}\sum_{h=1}^{H_t} p_{th} d_{jth}^{+} y_{jth}^{+}\right) \tag{11a}$$

subject to

$$\sum_{j=1}^{j_1} a_{rjt}^{+} x_{jt}^{+} + \sum_{j=j_1+1}^{n_1} a_{rjt}^{+} x_{jt}^{-} \le b_{rt}^{-}, r=1,2,...,m_1; t=1,2,...,T \tag{11b}$$

$$\sum_{j=1}^{j_1} a_{ijt}^{+} x_{jt}^{+} + \sum_{j=j_1+1}^{n_1} a_{ijt}^{+} x_{jt}^{-} + \sum_{j=1}^{j_2} a'_{ijt} \pm y_{jth}^{-} + \sum_{j=j_2+1}^{n_2} a'_{ijt} \pm y_{jth}^{+} \le \hat{w}_{ith}^{-}, i=1,2,...,m_2; t=1,2,...,T; h=1,2,...,H_t \tag{11c}$$

$$\sum_{j=1}^{j_1} a_{sjt}^{+} x_{jt}^{+} + \sum_{j=j_1+1}^{n_1} a_{sjt}^{+} x_{jt}^{-} + \sum_{j=1}^{j_2} a'_{ijt} + y_{jth}^{-} + \sum_{j=j_2+1}^{n_2} a'_{ijt} + y_{jth}^{+} \le b_{st}^{(p_s)}, \forall s \tag{11d}$$

$$0 \le x_{jt}^{-} \le x_{jtopt}^{+}, j=1,2,...,j_1; t=1,2,...,T \tag{11e}$$

$$x_{jt}^{+} \ge x_{jtopt}^{-}, j=j_1+1, j_1+2,...,n_1; t=1,2,...,T \tag{11f}$$

$$y_{jth}^{+} \ge y_{jthopt}^{-}, j=1,2,...,j_2; t=1,2,...,T; h=1,2,...,H_t \tag{11g}$$

$$0 \le y_{jth}^{-} \le y_{jthopt}^{+}, j=j_2+1, j_2+2,...,n_2; t=1,2,...,T; h=1,2,...,H_t \tag{11h}$$

where solutions of $x_{jtopt}^{-}(j=1,2,...,j_1)$, $x_{jtopt}^{+}(j=j_1+1, j_1+2,...,n_1)$, $y_{jthopt}^{+}(j=1,2,...,j_2$ and $h=1,2,...,H_t)$, and $y_{jthopt}^{-}(j=j_2+1, j_2+2,...,n_2$ and$h=1,2,...,H_t)$ can be obtained through solving submodel (11). Therefore, combining solutions of submodels (10) and (11), solution for the MSICCP model can be obtained as follows:

$$x_{jtopt}^{\pm} = \left[x_{jtopt}^{-}, x_{jtopt}^{+}\right], \forall j; t=1,2,...,T \tag{12a}$$

$$y_{jthopt}^{\pm} = \left[y_{jthopt}^{-}, y_{jthopt}^{+}\right], \forall j; t=1,2,...,T; h=1,2,...,H_t \tag{12b}$$

$$f_{opt}^{\pm} = \left[f_{opt}^{-}, f_{opt}^{+}\right] \tag{12c}$$

3. Case study

3.1. Overview of the case study

Consider a hypothetical case wherein an integrated biomass-MSW power plant is responsible for providing power for three regions over a one-year planning horizon (with four planning periods corresponding to four seasons of one year). The problem can be formulated as minimizing the expected cost of power generation activities in this power plant under environmental requirement during the four periods. Given a quantity of electricity that is promised to users, if the quantity is delivered, it will bring about net benefit to the local economy; however, if the promised quantity is not delivered, it will result in penalty on the local economy [28].

In the study system, three regions are located in the main grain producing areas which are rich in biomass resources. Among them, the main biomass category is agricultural residue which is straw and stalks from wheat in summer, maize and cotton in autumn. Different from the consumption of traditional fossil fuels, power generation with straw and stalks may reduce pollution and promote sustainable energy development, because of a lower emission of sulfur dioxide (SO_2), nitrogen oxides (NO_X) and soot. While, as is mentioned above, the availability of biomass is fluctuating or restricted according to the season. That means it is unrealistic to collect biomass feedstock continuously during the whole planning horizon. Moreover, large space is required to store the straw and stalks due to their low density. Therefore, warehouses are used for collecting and storing straw and stalks in order to maintain the normal operation of the plant in winter and spring. Furthermore, extra facilities with special devices for the transportation of straw and stalks would be also constructed. All these facilities must be well built against rain, moisture, fire and lightning [29].

Meanwhile, to reduce the risk of affecting the normal production due to the shortage of straw and stalks, MSW power generation is taken into consideration. However, the incineration process could generate many kinds of pollutants including heavy metals, acid gases (e.g. NO_X, SO_2), particulates, organic compounds that could cause negative effects on natural and human-living environment, such as ecotoxicity in soil, acidification, and photochemical ozone and so on [30]. In this study, dust, SO_2, NO_X and hydrochloric acid (HCl) are considered as the main air pollutants [31,32]. Besides, MSW is a heterogeneous material and its production rate and physical composition vary from place to place as they are a function of socio-economic level and climatic conditions [33].

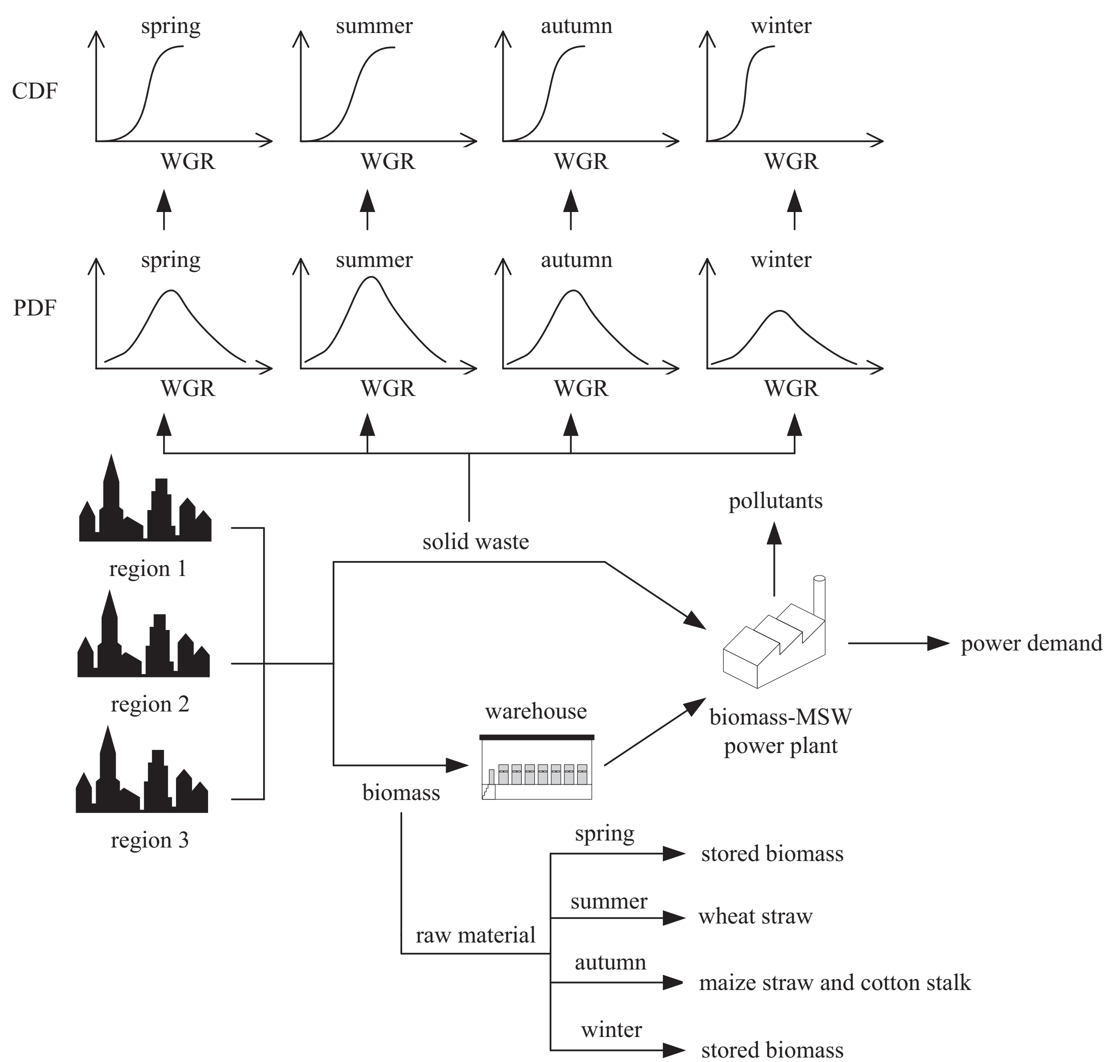

Fig. 2. The framework of the hybrid biomass-MSW power plant ("CDF", "PDF", and "WGR" denote "cumulative distribution function", "probability distribution function" and "waste generation rate").

Therefore, it assumes that the MSW generation rates of the three regions vary among different periods with a probability distribution.

In general, the study system (as shown in Fig. 2) is related to two kinds of energy resources, and conversion technologies, power demand activities, and various cost-effective demand-side management programs (e.g., mass transportation, storage, and power generation). Furthermore, multiple factors and processes are involved in the system, such as economic costs, emissions of pollutants, and power supply/demand, which are generally complex and associated with a variety of uncertainties.

3.2. Model development

The problems under consideration are: (a) how to effectively assign the power demand to the two power conversion technologies and minimize the system cost within a multistage context under uncertainties and complexities, (b) how to incorporate energy and environmental policies into the study problem with a low risk of system failure, (c) how to identify the allowable risk levels of violating the MSW constraints as the available amount of MSW is limited. The MSICCP method is useful for dealing with these problems. Therefore, a multistage stochastic inexact chance-constraint programming (MSICCP) model for power supply management of an integrated biomass-MSW power plant can be formulated as follows: the objective function is to minimize the expected value of system cost, which includes (a) cost for purchasing biomass feedstock and MSW, (b) operation cost for biomass power and MSW power, (c) cost for biomass storage, and (d) cost for air pollutant mitigation.

$$\min f^{\pm} = (a)+(b)+(c)+(d) \tag{13a}$$

$$(a) = \sum_{t=1}^{T}\sum_{h=1}^{H_t} p_{th} q_{th}^{\pm} PC_t^{\pm} + \sum_{t=1}^{T}\sum_{h=1}^{H_t} \frac{(W_{1t}^{\pm} + p_{th} Q_{1th}^{\pm}) FE_{1t}^{\pm}}{HE_{1t}^{\pm}} PW_t^{\pm} \tag{13b}$$

$$(b) = \sum_{k=1}^{K}\sum_{t=1}^{T} W_{kt}^{\pm} PP_{kt}^{\pm} + \sum_{k=1}^{K}\sum_{t=1}^{T}\sum_{h=1}^{H_t} p_{th} Q_{kth}^{\pm} PV_{kt}^{\pm} \tag{13c}$$

$$(c) = \sum_{t=1}^{T}\sum_{h=1}^{H_t} p_{th} ABA_{th}^{\pm} SC_t^{\pm} \tag{13d}$$

Table 1
Amount of biomass resource in the four periods (10^3tonnes).

Level	Probability	Amount of biomass resource $q_{th}^{\pm}$			
		$t=1$	$t=2$	$t=3$	$t=4$
Low (L)	0.2	[25.0, 30.0]	[30.0, 35.0]	[35.0, 40.0]	–
Medium (M)	0.6	[25.0, 30.0]	[35.0, 40.0]	[40.0, 45.0]	–
High (H)	0.2	[25.0, 30.0]	[40.0, 45.0]	[45.0, 50.0]	–

$$(d) = \sum_{k=1}^{K}\sum_{t=1}^{T}\sum_{h=1}^{H_t}\sum_{r=1}^{R} (W_{kt}^{\pm} + p_{th} Q_{kth}^{\pm}) \eta_{kr}^{\pm} \zeta_{kr}^{\pm} PTC_{rt}^{\pm} \tag{13e}$$

subject to:

(1) Municipal solid waste availability constraint

$$\Pr\left[\frac{(W_{kt}^{\pm} + Q_{kth}^{\pm}) FE_{kt}^{\pm}}{HE_{kt}^{\pm}} \le \mu Z \omega_t\right] \ge 1 - b_i, \forall t, h; k=1 \tag{13f}$$

(2) Mass balance constraint

$$ABA_{th}^{\pm} = q_{th}^{\pm} - \frac{(W_{kt}^{\pm} + Q_{kth}^{\pm}) FE_{kt}^{\pm}}{HE_{kt}^{\pm}}, \forall\ h; t=1, k=2 \tag{13g}$$

$$ABA_{th}^{\pm} = ABA_{(t-1)h}^{\pm} + q_{th}^{\pm} - \frac{[W_{kt}^{\pm} + Q_{kth}^{\pm}] FE_{kt}^{\pm}}{HE_{kt}^{\pm}}, \forall h, t \ge 2; k=2 \tag{13h}$$

(3) Environmental constraint

$$\sum_{k=1}^{K} (W_{kt}^{\pm} + Q_{kth}^{\pm}) \eta_{kr}^{\pm} \left(1 - \zeta_{kr}^{\pm}\right) \le TPD_{rt}^{\pm}, \forall t, h, r \tag{13i}$$

(4) Electricity demand constraint

$$\sum_{k=1}^{K} (W_{kt}^{\pm} + Q_{kth}^{\pm}) \ge D_t^{\pm}, \forall t, h \tag{13j}$$

Constraint (13f) can be specified as follows by introducing the cumulative probability:

$$\frac{(W_{kt}^{\pm} + Q_{kth}^{\pm}) FE_{kt}^{\pm}}{HE_{kt}^{\pm}} \le SW_t^{(b_i)}, \forall t, h; k=1 \tag{14}$$

where $f^{\pm}$ = the net expected system cost (¥); p_{th} = probability level of biomass resource for scenario h in period t; $q_{th}^{\pm}$ = the supply of biomass resource in scenario h during period t (kilotonne); $PC_t^{\pm}$ = the supply cost of biomass resource in period t (¥/tonne); $W_{kt}^{\pm}$ = the power production target of generator unit k in period t (GWh), where $k=1$ for MSW, $k=2$ for biomass; $Q_{kth}^{\pm}$ = the deficit of power production of generator unit k in period t (GWh); $FE_{kt}^{\pm}$ = the conversion efficiency of generator unit k in period t (10^9KJ/GWh); $HE_{kt}^{\pm}$ = heating value of energy resources utilized in generator unit k during period t (10^6KJ/tonne); $PW_t^{\pm}$ = the supply cost of MSW in period t (¥/tonne); $PP_{kt}^{\pm}$ = cost of allowable electricity generated by generator unit k in period t (10^6¥/GWh); $PV_{kt}^{\pm}$ = cost of excess electricity generated by generator unit k in period t (10^6¥/GWh); $ABA_{th}^{\pm}$ = amount of biomass stored in scenario h in period t (kilotonne); $SC_t^{\pm}$ = storage cost of biomass in period t (¥/tonne);

Table 2
Electricity generation targets and demand (GWh).

	b_i	Time period			
		$t=1$	$t=2$	$t=3$	$t=4$
$W_{1t}^{\pm}$ (MSW)	0.01	[85.00,95.00]	[90.00,100.00]	[85.00,95.00]	[70.00,80.00]
	0.05	[87.50,97.50]	[92.50,102.50]	[87.50,97.50]	[72.50,82.50]
	0.1	[90.00,100.00]	[95.00,105.00]	[90.00,100.00]	[75.00,85.00]
	0.2	[92.50,102.50]	[97.50,107.50]	[92.50,102.50]	[77.50,87.50]
$W_{2t}^{\pm}$ (Biomass)		[94.00,100.00]	[100.00,120.00]	[95.00,100.00]	[100.00,120.00]
Electricity demand $D_t^{\pm}$		[247.74,258.50]	[292.25,305.68]	[275.00,275.40]	[255.14,263.64]

Table 3
Municipal solid waste availability under different b_i levels (10^3tonnes).

	b_i value												
	0.01	0.05	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	0.95	0.99
$t=1$	110.1	112.6	115.1	117.8	120.5	123.4	126.5	129.8	133.3	136.2	138.1	139.8	141.1
$t=2$	145.6	148.1	150.6	153.1	156.6	160.3	164.2	167.9	171.4	174.7	176.7	178.2	179.4
$t=3$	122.3	124.8	127.3	129.8	132.5	135.4	138.5	141.8	144.7	147.4	148.9	150.2	151.3
$t=4$	113.5	116.0	118.5	121.0	123.3	125.4	127.3	129.0	130.5	131.8	132.9	133.9	133.8

Table 4
The cost of allowable and excess electricity generation (10^6¥/GWh).

	$t=1$	$t=2$	$t=3$	$t=4$
Cost of allowable electricity generation $PP_{kt}^{\pm}$				
$k=1$	[0.20, 0.30]	[0.38, 0.48]	[0.30, 0.40]	[0.29, 0.39]
$k=2$	[0.35, 0.43]	[0.50, 0.55]	[0.40, 0.45]	[0.42, 0.49]
Cost of excess electricity generation $PV_{kt}^{\pm}$				
$k=1$	[0.28, 0.48]	[0.53, 0.63]	[0.36, 0.55]	[0.47, 0.74]
$k=2$	[0.50, 0.65]	[0.70, 0.80]	[0.46, 0.76]	[0.60, 0.86]

$\eta_{kr}^{\pm}$ = the emission intensity of pollutant r from generator unit k (tonne/GWh), where $r=1$ for dust, $r=2$ for SO_2, $r=3$ for NO_X, $r=4$ for HCl; $\zeta_{kr}^{\pm}$ = the removal efficiency of pollutant r from generator unit k; $PTC_{rt}^{\pm}$ = the removal cost of pollutant r in period t (¥/tonne); μ = the proportion of MSW incineration; Z = the total amount of population of three regions; ω_t = the generation rate of MSW in period t; b_i = probability of default; $TPD_{rt}^{\pm}$ = the allowable emissions of pollutant r in period t (tonne); $D_t^{\pm}$ = the demand of electricity in period t (GWh); SW_t = the MSW availability in period t (kilotonne).

Data used in the analysis stem from multiple sources including statistical reports, other related literatures, regulations, policies, and case studies. Table 1 provides the available biomass resource in the three regions and the associated probabilities of occurrence during the four planning periods. Table 2 describes the power generation targets for MSW and biomass and the total electricity demand during the planning periods. Table 3 shows the availability of MSW over the planning horizon under different b_i levels. In the three regions, if power supply cannot sufficiently meet the end-users' demands, decision makers would have to put extra funds into purchasing more energy resources at raised prices in response to the deficiencies of electricity productions. Then, economic penalties would be incurred. Table 4 present the cost of allowable and excess electricity generation.

4. Results analysis and discussions

The objective of the MSICCP model is to minimize the expected value of the costs under two kinds of energy resources over the planning horizon. Solutions provide an effective linkage between the predefined energy and environmental policies and the associated economic implications (e.g., losses and penalties caused by improper policies) within a multistage context. The solutions contain a combination of deterministic, interval and distributional information, and can thus facilitate the reflection for different forms of uncertainties [34]. The interval solutions can help managers obtain multiple decision alternatives, as well as provide bases for further analyses of tradeoffs between system cost and electricity production; the continuous variable solutions are related to decisions of electricity generation, deficits of electricity and biomass storage.

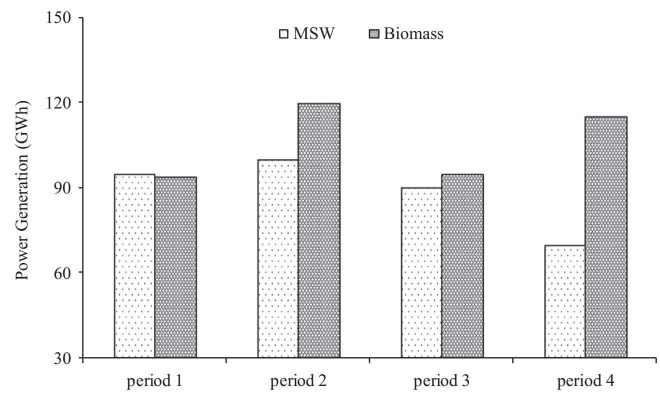

Fig. 3. Allowable power generation in the four periods.

Fig. 3 shows the optimized electricity generation targets of biomass and MSW power (taken $b_i=0.01$ as an example). The generation quantity of biomass power would be 94.00, 120.00, 95.06, and 115.14 GWh from period 1 to period 4, respectively. Meanwhile, as constraint for control of air-pollutants emission would be added in the developed MSICCP model, the electricity generated by MSW would respectively be 95.00, 100.00, 89.97, and 70.00 GWh under period 1, period 2, period 3 and period 4, which would not significantly increase due to its high SO_2, NO_X and HCl emission rates. Moreover, the results indicated that the electricity would be generated primarily by biomass that associated with low pollutants-emission rates. In addition, as shown in Table 2, the optimized electricity generation of MSW power would reach to its upper target level during period 1 and 2, then lower target level in period 4; and for the optimized electricity generation of biomass power, it would reach to its upper target level in period 1 and lower target level in period 2.

Fig. 4 displays the amount of biomass stored under all possible 22 scenarios during the planning periods under the consideration of $b_i=0.01$. Generally, a biomass power plant has to collect adequate biomass fuel to maintain the normal production. Besides, it is necessary to store enough biomass material to ensure that it could operate continuously and the storage level has to be kept within certain limits. Under this case, the amount of biomass stored at the end of period 1 (one scenario actually) would be $[5.33, 10.66] \times 10^3$ tonnes under the initial biomass resource level (probability is 100%). When the biomass resource level is under the low, medium and high levels in period 2 (joint probabilities are 20%, 60% and 20%), the amount of stored biomass would be $[9.61, 20.18] \times 10^3$, $[14.61, 25.18] \times 10^3$ and $[19.61, 30.18] \times 10^3$ tonnes, respectively. When the biomass resource levels are under the low and high levels in period 2, and low, medium and high in period 3 (joint probabilities are 4%, 12% and 4%), the amount of stored biomass would be stabilized at $[24.60, 40.54] \times 10^3$ and $[44.60, 60.54] \times 10^3$ tonnes; and when the biomass resource levels are

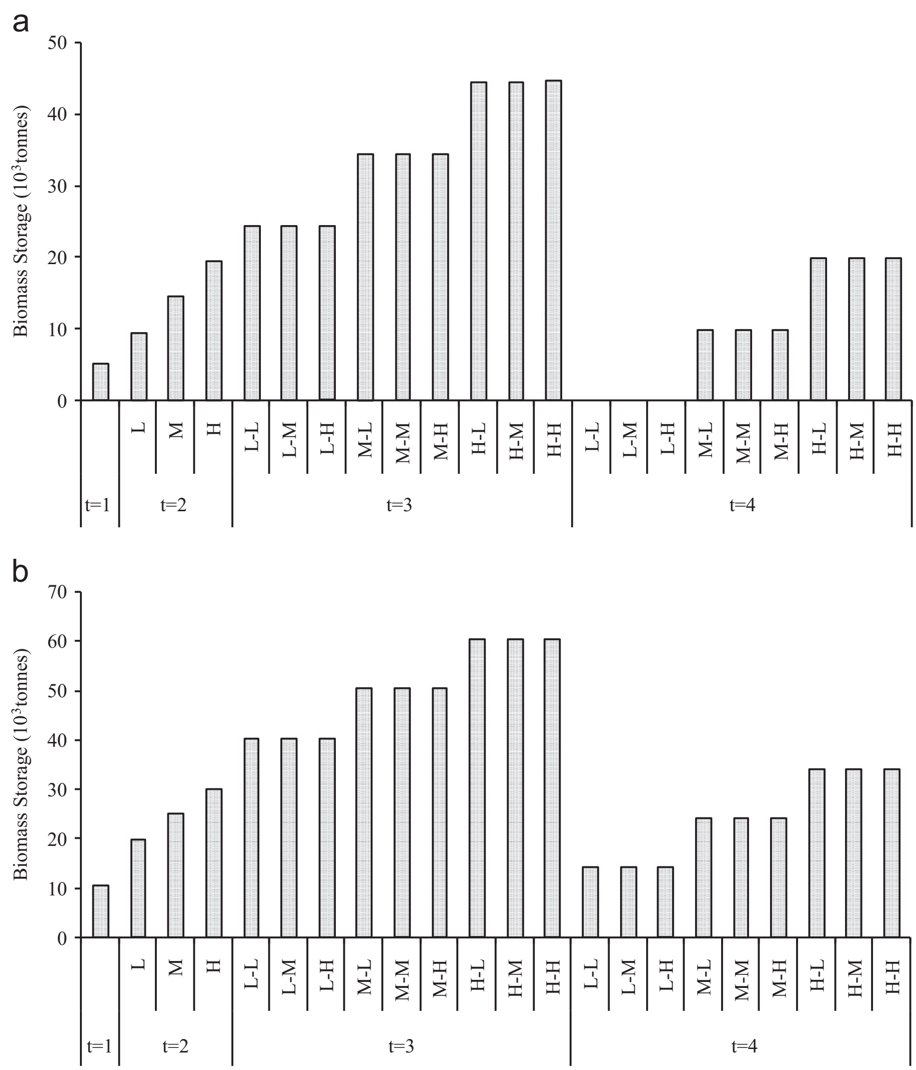

Fig. 4. Amount of biomass stored under different scenarios.

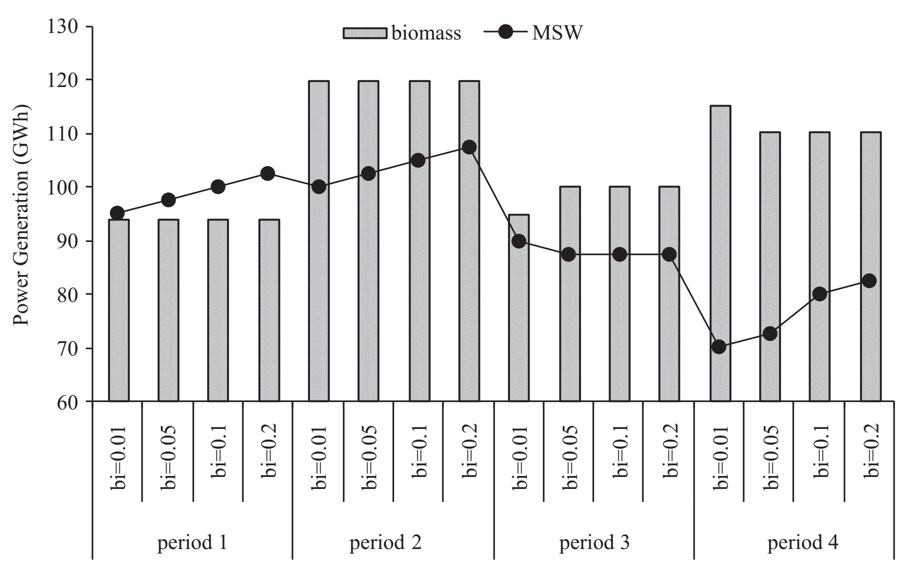

Fig. 5. Allowable power generation of biomass and MSW under four b_i levels.

medium in period 2, and low, medium and high in period 3 (joint probabilities are 12%, 36% and 12%), the amount of stored biomass would be stabilized at $[34.60, 50.54] \times 10^3$ tonnes. In period 4, as the amount of biomass resource is 0 and the probability of biomass resource level is 100% (as shown in Table 1), scenarios and joint probability of each scenario are the same as period 3. Accordingly,

the amount of biomass stored at the end of period 4 would be stabilized at $[0.00, 14.36] \times 10^3$, $[20.00, 34.36] \times 10^3$ and $[10.00, 24.36] \times 10^3$ tonnes.

In comparison with the results under periods 2 and 3, there is a relative small amount of stored biomass in periods 1 and 4. Two reasons account for this. On one hand, the biomass material such as straw and stalks is rather abundant in the study areas during periods 2 and 3, which provides a possible reason for storing a huge amount of biomass. However, there is almost no available biomass fuel in periods 1 and 4 that it's unrealistic to store biomass material as much as periods 2 and 3. On the other hand, as shown in Fig. 3, the amount of electricity generated by biomass in period 4 is so huge that it's nearly equal to period 3, which offers another explanation.

Compared the two power generation technologies' contribution to the electricity demand, it indicates that different power conversion technologies have varied generation quantities under different b_i levels. As the previous section analysis, biomass power plays an important role in the electricity generation activities during the whole planning horizon. This is mostly attributable to the policies of all purchase and preferential price to biomass power carried out by decision-makers, which offer a potential opportunity and bright future for the rapid development of biomass power.

Fig. 5 describe the optimized electricity generation targets of biomass and MSW during the four periods (under four b_i levels). Generally, as b_i value increasing, the electricity production of biomass power would be stable while it would keep the increasing trend for MSW power during the same period. For example, in period 2, the total amount of biomass power would be stabilized at 120.00 GWh under different b_i levels; and for MSW power, it would be 100.00, 102.50, 105.00, and 107.50 GWh when the values of b_i increase from 0.01 to 0.2, respectively. This is because the MSW availability would increase along with the increasing b_i (as shown in Table 3). However, there are also some exceptions. One is the electricity generated by biomass would be 95.06, 100.00, 100.00, 100.00 GWh (in period 3) and 115.14, 110.27, 110.27, 110.27 GWh (in period 4) under b_i=0.01, 0.05, 0.1 and 0.2, respectively (as shown in Fig. 5). The trough in period 3 is mainly attributable to the higher variable cost of biomass power (as shown in Table 4), and the main reason for the peak in period 4 is the amount of MSW power would be 70.00 GWh which would reach its lower target level (as shown in Table 2). Another exception is the peak under b_i=0.01in period 3 when the amount of MSW power would be 89.97 GWh (as shown in Fig. 5). The main reason is that the electricity demand in period 3 is relative higher compared with periods 1 and 4, and lower than period 2. Another explanation is that the amount of biomass power would be

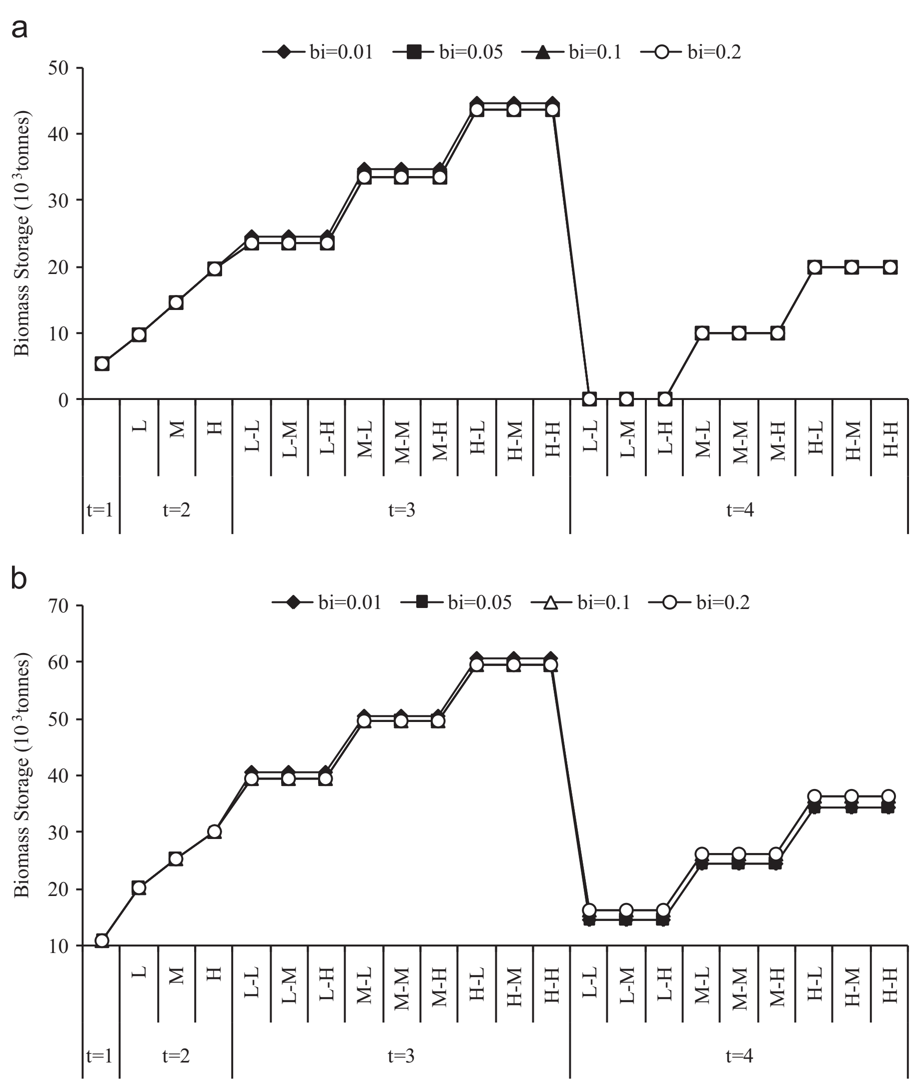

Fig. 6. Amount of biomass stored in different scenarios under four b_i levels.

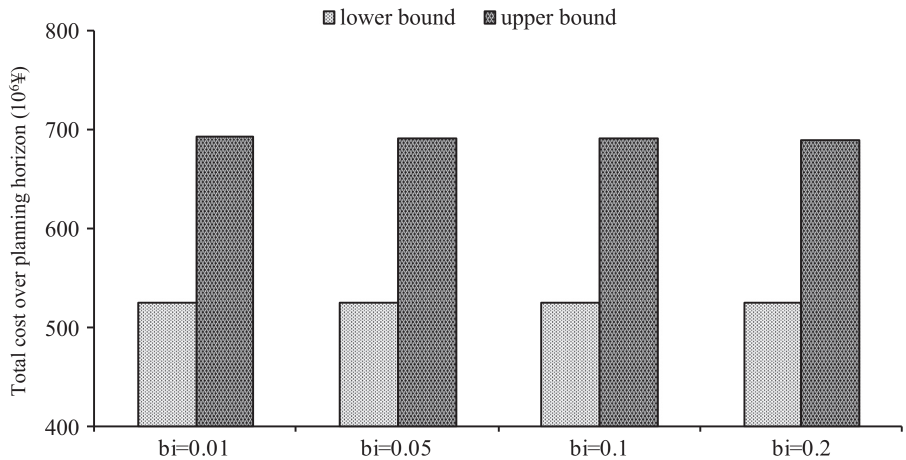

Fig. 7. Costs under four b_i levels.

95.06 GWh under b_i=0.01 which would almost reach its lower target level in period 3(as shown in Table 2).

Deficits would occur if the available generation targets cannot meet the electricity demand. In general, different power conversion technology has varied excess generation quantities under changed possible scenarios. For example, when b_i takes value of 0.01, the excess generation quantities would be stabilized at 0, 0, [0, 0.40], [0, 8.50] GWh for biomass power and [58.74, 69.50], [72.25, 85.68], 89.97, 70.00 GWh for MSW power during the four periods. Besides, the deficits of electricity would fluctuate along with different b_i in the same period, respectively. Taking period 4 as an example, the excess generation quantities would be stabilized at [0, 8.50], [0, 8.37], 0, 0 GWh for biomass power and 70.00, [72.37, 72.50], [64.87, 73.37], [62.37, 70.87] GWh for MSW power under b_i=0.01, 0.05, 0.1 and 0.2, respectively. The results indicate that change in b_i would lead to different electricity deficits of the two generator units. In case of insufficient electricity supply, MSW power would first be chosen as the recourse action to compensate the deficits over the planning horizon, while the biomass power conversion technology would only be supplement. This is because MSW power conversion technology has relatively low operating and penalty costs and comparatively low capital cost for electricity generation.

The purpose of biomass storage is for the sustainable development of biomass power and in case of unexpected situations which would threat the normal operation of this plant. Fig. 6 presents the amount of biomass stored in all possible 22 scenarios under four b_i levels during the planning periods. It indicates that as b_i value increasing, the amount of stored biomass would be stable in periods 1 and 2, while it would have no significant fluctuation during periods 3 and 4. Taking period 3 as an example, when the biomass resource levels is low in period 2, and low, medium and high in period 3 (joint probabilities are 4%, 12% and 4%), the amount of stored biomass would be [24.60, 40.54] $\times 10^3$, [23.56, 39.52] $\times 10^3$, [23.56, 39.52] $\times 10^3$ and [23.56, 39.52] $\times 10^3$ tonnes when b_i takes values of 0.01, 0.05, 0.1 and 0.2, respectively. When the biomass resource levels are medium in period 2, and low, medium and high in period 3 (joint probabilities are 12%, 36% and 12%), the amount of stored biomass would be [34.60, 50.54] $\times 10^3$, [33.56, 49.52] $\times 10^3$, [33.56, 49.52] $\times 10^3$ and [33.56, 49.52] $\times 10^3$ tonnes under b_i=0.01, 0.05, 0.1 and 0.2, respectively; and when the biomass resource levels are high in period 2, and low, medium and high in period 3 (joint probabilities are 4%, 12% and 4%), the amount of stored biomass would be [44.60, 60.54] $\times 10^3$, [43.56, 59.52] $\times 10^3$, [43.56, 59.52] $\times 10^3$ and [43.56, 59.52] $\times 10^3$ tonnes under b_i=0.01, 0.05, 0.1 and 0.2, respectively. The results indicate that the biomass power is a reliable electricity resource due to it relatively has no pollutant emission in the power conversion process compared with MSW power.

Fig. 7 shows the detailed system cost under four b_i levels over the planning horizon. It includes expenses for energy resources supply, biomass materials storage, power generation operation and operating costs for air-pollution control techniques. The total system cost would be [525.00, 692.74] $\times 10^6$, [524.72, 692.25] $\times 10^6$, [524.86, 690.62] $\times 10^6$ and [524.64, 689.83] $\times 10^6$¥ under b_i=0.01, 0.05, 0.1 and 0.2, respectively. It is indicated that the total system cost would decrease slightly as b_i value increasing. The main reason is that the excess generation quantities of biomass power would have a significant reduction under all possible scenarios along with increasing b_i levels, especially in period 4, which would gradually be replaced by MSW power with low operating and penalty costs.

From the above analyses, it is indicated that the solutions obtained from the MSICCP model are able to supporting (a) adjustment or justification of allocation patterns of energy resources and services, and (b) analysis of interactions among economic cost, environmental requirement, and power supply security [15]. The interval solutions are effective to generate decision alternatives which represent various options reflecting system cost-production tradeoffs.

5. Conclusion

A multistage stochastic inexact chance-constraint programming (MSICCP) model has been developed for supporting effective power supply management planning under uncertainty. This method is based on an integration of multistage stochastic programming (MSP), interval-parameter programming (IPP), and chance-constraint programming (CCP). It allows uncertainties presented as both probability distributions and interval values to be incorporated within a multi-facility, multi-period, and multi-option context. Besides, penalties are exercised with recourse against any infeasibility, which permits in-depth analyses of various policy scenarios that are associated with different levels of economic consequences when the promised electricity generation targets are violated [35]. Dynamics and uncertainties of biomass resource availability (and thus electricity shortage) could be taken into account through generation of a set of representative scenarios within a multistage context. Moreover, the generated solutions can be used for examining various decision options that are associated with different levels of risks when the availability of MSW is limited. Probabilistic distributions of MSW can be integrated into the optimization process through the introduction of

chance-constrained program (CCP) under a series of b_i levels. The interval solution under different b_i levels can be used for generating multiple decision alternatives, which would be useful for analyzing tradeoffs between system costs and constraint-violation risks.

The developed MSICCP model has been applied to plan the development of an integrated biomass-MSW power plant, and manage the power supply based on varied energy resources. In general, it could provide rather stable solutions which contain a combination of deterministic, interval and distributional information, and can thus facilitate the reflection for different forms of uncertainties. Although this study is the first attempt for planning energy resources in power supply management through development of an MSICCP approach, the results suggest that this technique is effective and can be extended to other environmental problems where complex uncertainties exist in a long planning period. Besides, it is also possible that other programming techniques (such as fuzzy programming and dynamic programming) be integrated with MSICCP for handling more complicated cases [23].

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